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Plane detection of polyhedral cultural heritage monuments: The case of tower of winds in Athens

Evangelos Maltezos*, Charalabos Ioannidis

Lab. of Photogrammetry, School of Rural and Surveying Engineering, National Technical University of Athens, 9 Iroon Polytechniou St., Athens, Greece, 15780

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ABSTRACT

This study introduces an efficient and easy to implement plane detection approach towards the extraction of high-level information from 3D point clouds associated with polyhedral cultural heritage monuments. An adapted version of the randomized Hough transform (RHT) called "adaptive point randomized Hough transform" (APRHT) and a multiscale framework in terms of Level of Detail 1 (LoD 1) and LoD 2 are proposed. A dense image matching point cloud of an octagonal tower called Tower of Winds, which is situated on the northern foot of the Acropolis hill in Athens was used. A pre-process is carried out to extract points associated with the vertical structural elements. Then a plane detection process is performed in terms of LoD 1 to calculate the plane parameters (θ, φ and ρ) of each of the eight planar surfaces using a coarse form of the entire monument, that is, a sparse point cloud extracted via subsampling process. A mask of one representative detected planar surface is used to clip the initial point cloud with the initial point density. Then, a second plane detection process in terms of LoD 2 at the clipped point cloud is implemented to calculate the corresponding accurate plane parameters. The results are useful for cultural heritage preservation purposes and illustrate the robustness, efficiency and the rapidity of the proposed framework.

1. Introduction

The introduction of the new laser technologies and sophisticated computer vision techniques, contribute to the extraction of interesting information from cultural heritage sites for both structural and historical purposes. In this context, several interesting and efficient studies have been implemented that use point clouds obtained from Aerial and Terrestrial Laser Scanning [Awrangjeb and Fraser 2013; Ait el kadi et al. 2015; Markiewicz et al. 2015; Barsanti et al. 2017]. Dense Image Matching (DIM) point clouds and Unmanned Aerial Vehicles (UAVs) have been also utilized for the 3D geometric documentation of cultural heritage sites [Maltezos and Ioannidis 2014]. Over the past years more and more researchers have developed robust matching cost functions and stereo matching algorithms applying DIM [Hirschmüller and Scharstein 2009; Remondino et al., 2013; Stentoumis et al. 2014]. DIM technique is not only a flexible and attractive solution to produce accurate and high qualitative photogrammetric products but also is a major contribution to cost effectiveness [Stentoumis et al. 2013; Grenzdörffer et al., 2015; Stathopoulou et al., 2015; Vincent et al. 2015; Doulamis et al. 2015; Teza et al. 2016; Themistocleous et al., 2016].

1.1. Previous work for plane detection

The automatic segmentation or plane detection from a 3D point cloud (either extracted by laser technologies or by DIM stereo methods) is a research topic of high interest. Point cloud or mesh segmentation in cultural heritage is fundamental in order to 1) manage the complexity of reality-based models by selectively simplifying the most suitable level of each segment, 2) maintain the maximum level of detail only on the more detailed sections, and 3) separate load-sustaining elements apart from ornamental ones [Barsanti et al. 2017]. The main applications of the automatic plane detection either at typical historic buildings or at polyhedral cultural heritage monuments are 1) detection of significant changes and destructions for 4D applications, 2) 3D modeling and surface reconstruction of roofs and facades, 3) preservation and structural analysis, and 4) accurate plane projection for orthoimages [Artese and Gencarelli 2008; Armesto et al. 2010; Spina et al., 2011; Ait el kadi et al. 2013; He et al. 2013; Teza and Pesci 2013; Ait el kadi et al. 2015; Fryskowska et al. 2015; Markiewicz et al. 2015; Brodovskii et al. 2016; Chiabrando et al. 2016; Malihi et al. 2016; Barsanti et al. 2017; Dore and Murphy 2017]. The mostly used data driven (also known as bottom-up) plane detection techniques are region growing, RANSAC and Hough methods [Vosselman et al. 2004;

* Corresponding author.
E-mail addresses: maltezosev@gmail.com (E. Maltezos), cioannid@survey.ntua.gr (C. Ioannidis).

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Schnabel et al. 2007; Tarsha-Kurdi et al. 2007; Borrmann et al. 2011].The region growing algorithm seeks to the aggregation of points into segments according to certain homogeneity criteria. Although this technique provide efficiency, is influenced by the presence of noise at the identification of the seed surface and the growing phase [Ait el kadi et al. 2015]. The clustering principle requires important computational time for multi-dimensional data (3D) and is also sensitive to noisy data. Profiling segmentation technique also present some considerable potential but is not appropriate to unstructured data characterized by varying densities [Mapuris and Sithole 2012; Ait el kadi et al. 2015]. The RANSAC and Hough methods define the best plane fitting primitives to a point cloud. A common assumption when applying these techniques is that the object of interest is a polyhedron that is reconstructed from planar patches derived from plane detection techniques. One of the most efficient Hough methods is the 3D Randomized Hough Transform (RHT). The advantages of the RHT in comparison with the 3D Standard Hough Transform (SHT) and RANSAC have highlighted by [Borrmann et al. 2011; Maltezos and Ioannidis 2016]. The RHT not only is robust against various defects such as occlusions and missing data but also satisfies greatly the accuracy vs. computational time tradeoff. Further interesting studies that propose efficient segmentation and plane detection techniques on 3D point clouds can be found by [Steiner et al., 2004; Deschaud and Goulette 2010; Nguyen and Le 2013; Feng et al. 2014; Shui et al. 2016; Grilli et al., 2017].

1.2. Our contribution

Traditionally, the detection of the planes of polyhedral cultural heritage monuments was performed by measuring corner points using surveying techniques (Total Stations) or on Digital Photogrammetric Workstations (DWPs). To avoid the ambiguity caused by the manual selection of these points as well as to reduce the cost and the computational time, the modern approaches utilize 3D point clouds and apply automatic plane detection techniques. The contribution of this study is to introduce an efficient and rapid plane detection approach towards the extraction of high-level information from 3D point clouds associated with polyhedral cultural heritage monuments. In this context, an adapted version of the RHT called “adaptive point randomized Hough transform” (APRHT) and a multiscale framework in terms of LoD 1 and LoD 2 are proposed. A dense DIM point cloud of the Tower of Winds which is an important and unique monument is used for the implementation of the proposed framework. A desktop computer (CPU with 3.20 GHz/12G Memory/graphic card NVIDIA Quadro FX 4600) and the MATLAB computing environment are used to process the dataset.

2. Calculation

2.1. Plane detection technique

In this study the plane detection process was conducted by using two variations of the RHT. The first variation is the extended randomized Hough transform (ERHT) analyzed by [Maltezos and Ioannidis 2016]. The second variation is an adapted version of the ERHT called “APRHT”. There are fundamental differences between the ERHT and the APRHT. For the ERHT, the selection of the 3 points is randomly performed using all the remaining point cloud in each iteration. Also, the points of the 3D point set that are close to the detected plane are removed using only a distance tolerance. For the APRHT, the proposed novelties are associated with:

1. *The automatic selection of a sub-region surround an adaptive center point*. The selection of the sub-region surround each adaptive center point facilitates the selection of the 3 points. Thus, the possibility of the selection of 3 points from homogeneous regions is increased, while, the selection of noisy points (e.g., remaining points due to the removal of the assigned points of each detected plane) is avoided.
2. *The automatic descent tuning process of parameters*. The automatic descent tuning of parameters ensures the accurate and reliable detection of the prominent planes. Commonly, to decrease the computational time a loose parameterization is used. However, this significantly affects the accuracy. Using the automatic descent tuning process, strict initial values of the parameters associated with the size of the sub-region surround each adaptive center point, constraint criteria and accumulator may be primarily selected. Then, the parameterization may be gradually loosen using a predefined threshold associated with the used number of adaptive points. Therefore, a balance between the computational time and the accuracy is achieved.
3. *The removal of points that fulfil a distance tolerance and an additional normal tolerance regarding the detected plane*. The combined use of the distance and normal tolerances contributes to the proper assignment of points on the detected prominent planes. This is particularly useful for noisy point clouds as well as for cases of edges (i.e., intersections of planar surfaces) where the orientation of the normal vectors changes abruptly. Further, relieves the accumulator from unnecessary planes.

The aforementioned novelties not only decrease significantly the computational time for the detection of the prominent planes but also improve the corresponding accuracy; further, cases of under-segmented, over-segmented and spurious planes are eliminated. As mentioned before, the ERHT does not embody the normal tolerance. The normal tolerance significantly affects the accuracy of the plane detection results especially for noisy point clouds and surfaces to whom orientation (i.e., the normal vector) changes abruptly. To highlight the normal tolerance's impact to the plane detection accuracy, a third variation of the RHT was conducted called enhanced-ERHT (eERHT). The eERHT is an enhanced version of the ERHT that embodies not only the distance tolerance while discarding the points that referred to the detected plane but also the normal tolerance. On the other hand, two approaches of the APRHT are explored. In the first approach, called APRHT-C, the adaptive center point is randomly selected from a predefined and constant downsampled 3D point cloud extracted by the initial point cloud. Each downsampled point is characterized as a “key” point. Thus, the downsampled 3D point cloud should describe in a very generic form the object of interest. In the second approach, called APRHT-R, the adaptive center point is randomly selected from the remaining points of the 3D point set in each iteration. Table 5 indicates the used algorithm variations and their selected parameters.

Fig. 1 depicts the algorithm flow of the APRHT. The algorithm starts with a random and automatic selection of an adaptive point from the 3D point set. Then, a sub-region surrounding the adaptive point is selected using a search area with a predefined radius (R_srg). The sub-region should consist of a sufficient number of points in order to efficiently detect the prominent planes. Then, the selection of 3 points, p_1, p_2 and p_3, from the sub-region that fulfil the geometric constraint criteria (described in detail below) is performed. The parameters θ, φ and ρ of the plane that the 3 points define are calculated and are stored at the accumulator increasing the corresponding cell. If the prerequisites of the design of the accumulator are fulfilled in the corresponding cell, a prominent plane is detected. A simple and effective design of the accumulator as described in detail below is implemented. If the number of the used adaptive points is over a predefined counter threshold (C_adp), the automatic descent tuning process of parameters is performed. The points of the total 3D point set that fulfil a distance tolerance (D_thr) and a normal tolerance (N_thr) regarding the detected plane are removed and the accumulator is reset. The above procedure continues for a predefined number of iterations *i* until no points (or few points using a predefined stopping rule) at the 3D point set will remain.